

Abstract

Building 3D models of real-world objects by assembling views taken by a range sensor promises to be a more efficient method than manually producing CAD drawings. In this technique, a series of range images are acquired and then registered, or aligned, with each other to a high degree of accuracy. Finally, the polygonal meshes corresponding to the range images are merged to form a complete 3D model consisting of a single mesh.

Many techniques have been proposed to solve the registration problem; however, little work has been done to date to compare several registration algorithms with the same sets of data. In this work, we examine a software test-bed built for performing such comparisons. Within this test-bed, we have implemented several common registration algorithm variants to the baseline *Iterative Closest Point (ICP)* algorithm and tested them on partially overlapping range images taken from four different objects.

Techniques Implemented

ICP Objective:
Align two surfaces by iteratively finding the rigid transformation that minimizes

$$f(\mathbf{R}, \mathbf{T}) = \sum_{i=1}^N w_i \|x_i - \mathbf{R}p_i - \mathbf{T}\|^2$$

where w_i is typically given by

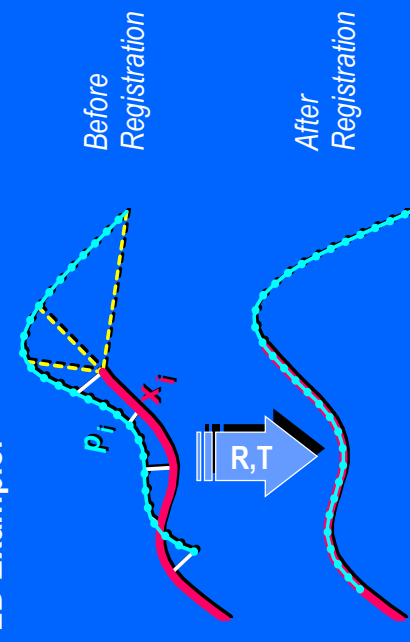
$$w_i = \begin{cases} 1 & \|x_i - p_i\|^2 < D_{\max} \\ 0 & \text{else} \end{cases}$$

for some maximum allowed point pair distance, D_{\max}

Algorithm Pseudo-Code:

Repeat
Find corresponding point pairs, $\{(p_i, x_i)\}$
Assign weights to each pair, $\{w_i\}$
Compute the optimal transformation to minimize $f(\mathbf{R}, \mathbf{T})$
Until $f(\mathbf{R}, \mathbf{T})$ ceases to change significantly

2D Example:



P_i , the cyan curve, is being registered to X , the red curve. Thin solid white lines connect corresponding point pairs. Thin dashed yellow lines represent outlier pairs.

Schütz's Outlier Classifier

$D_{\max} = (c \cdot s \cdot r)$
where $s \cdot r$ is the typical Euclidean distance between neighboring samples, and c is a dynamic tuning parameter that is decreased as the two surfaces become closer.

Range Images Evaluated



Parameter Settings and Results

Uniform Decimation Factor

Factors used:
• 1, 2, 4, 8, 16, and 32

Results:
• Factors greater than 2 produce noticeably worse registration results.

Loop Criterion

Criteria used:
• 0.3, 0.03, and 0.003mm

Results:
• Tighter thresholds require more iterations and produce better results.

(Baseline parameter values given in bold)

Outlier Classifier

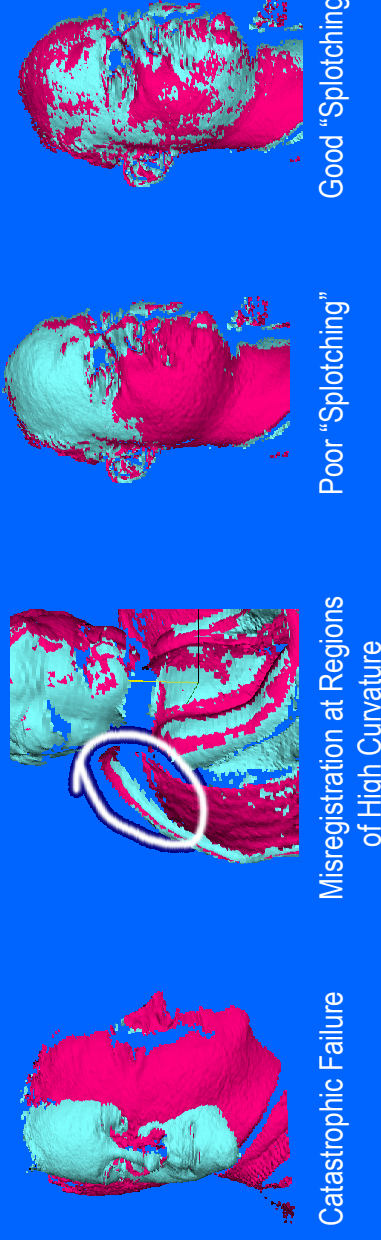
Parameter values (D and $s \cdot r$):

- 7.1, 3.6, 1.8, 0.9, 0.4, 0.2, and 0.1mm

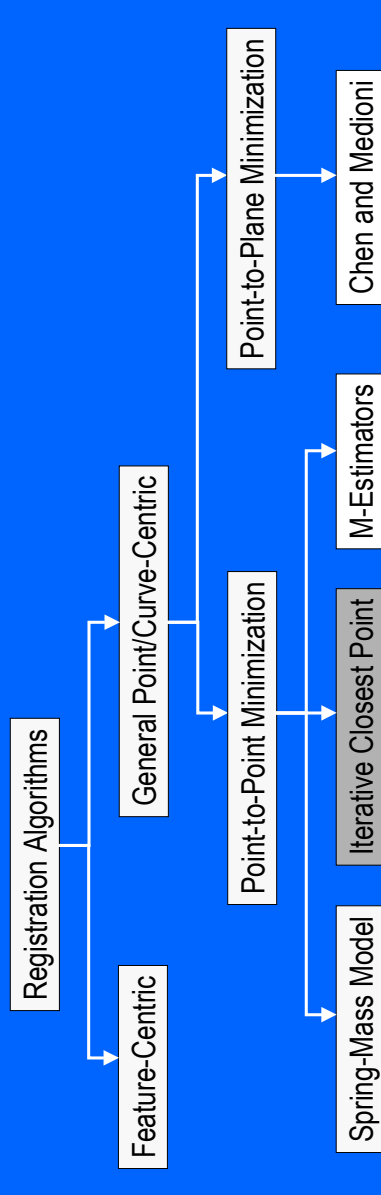
Results by classifier type:

- None
Catastrophic failure when significant non-overlapping regions exist.
- Schütz's
Avoids catastrophic failures with proper parameter settings.
- Zhang's
Typically yields the best results. Often works best when D is set so low that the $D_{\max} = \xi$ condition is always selected.

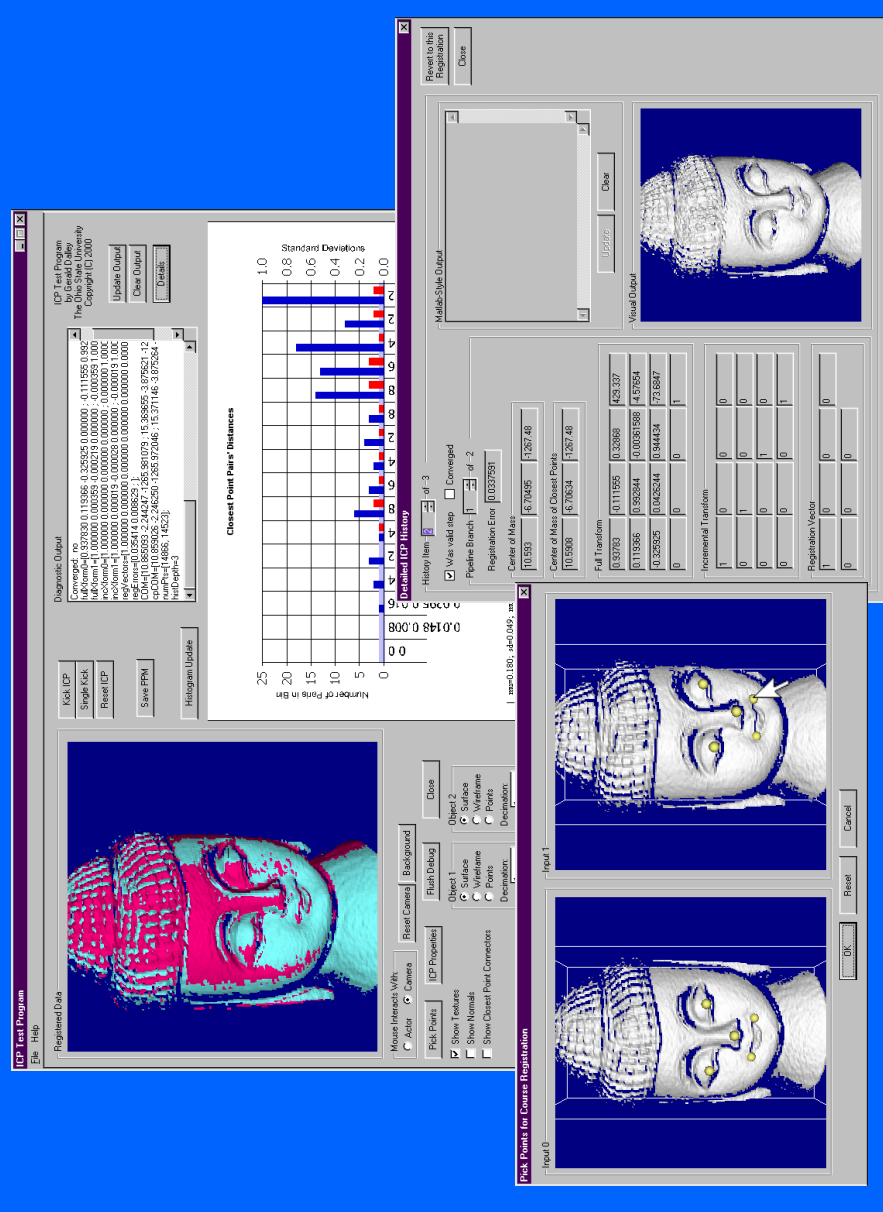
Classification of Output



Partial Taxonomy of Common Registration Techniques



Testbed GUI



These images are screenshots of the GUI implemented to configure the tests and evaluate the results.

Future Work

- Test alternate registration algorithms
- Chen and Medioni's (in progress)
- M-Estimators
- ICP with point-to-interpolated point correspondence
- Iterative Spring-Mass Systems

- Perform ground-truth tests (in progress)
- Evaluate effects of non-uniform decimation
- Perform registration with non-sphere topological objects
- Extend the software testbed

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